

MODELING CLIMATE-FIRE CONNECTIONS WITHIN THE GREAT BASIN AND  
UPPER COLORADO RIVER BASIN, WESTERN UNITED STATES

by

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# The University of Utah Graduate School

## STATEMENT OF THESIS APPROVAL

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## ABSTRACT

The Great Basin and Upper Colorado River Basin of the Western United States possess complex topography and varied fire ecology. The specific precipitation and temperature patterns that may increase the likelihood of fire occurrence and severity in this region are poorly understood. This study used antecedent climate patterns to identify the conditions prior to fire occurrence and to construct a model of fire risk and severity for the Interior Western United States. Data from the Monitoring Trends in Burn Severity (MTBS) dataset spanning a period from 1984 to 2009 were used to understand spatial and temporal trends in fire. Parameter-elevation regressions on independent slopes model (PRISM) data were used to represent climatic conditions across the study area during this time period, based on monthly maximum temperature, precipitation and drought severity. These data revealed five fire-climate patterns which exist within the region; three of the patterns are characterized by predominantly dry conditions and two by predominantly wet conditions during the months prior to a fire. Maximum entropy modeling was used to characterize the spatial patterns of fire-climate classes and predict future fire conditions, and classification trees were used to examine burn severity. A test dataset of fires which occurred within the study region during 2010 were predicted with an average area under curve (AUC) score of 0.945. Results from modeling burn severity were less robust, but do provide a risk assessment based on current and antecedent climate conditions. This modeling approach is aimed at providing land managers a practical way to assess current and future fire conditions at a relatively fine spatial scale given the current infrastructure and availability of climate data.

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## INTRODUCTION

Fire is a process unique to Earth. It is here that all three elements required to sustain combustion (ignition source, fuel, and oxygen) combine. Fire has shaped many of the landscapes seen throughout the temperate regions of the world, and has established itself as an essential ecological component within these regions (Pyne, Andrews, & Laven, 1996). Federal land-management agencies consistently spend over a billion dollars annually on wildland firefighting efforts. These expenditures can only be expected to rise with the recent increase in large fires throughout the West (Stephens, 2005).

While previous investigations into climate and fire have examined the general spatial and temporal relationships between fire occurrence and climate conditions (Littell, McKenzie, Peterson, & Westerling, 2009; Trouet, Taylor, Wahl, Skinner, & Stephens, 2010; Westerling, Gurshunov, Brown, Cayan, & Dettinger, 2003), research on specific climatic patterns related to specific fires remains sparse. This study explored the importance of local-scale processes by examining climate-fire relationships on a shorter, finer time scale and within a smaller area compared to previous research. Accomplishing this involved focusing on the conditions leading up to individual fires, in addition to the broader trends associated with burned area across the entire study area. Studying wildfire in this way allows for the investigation into the linkages between climate and fire across space and through time.

This study used antecedent climate conditions to characterize and model fire occurrence and fire severity based on data derived from known fires exceeding 1,000 acres in size between 1984-2009. Multiple gridded datasets representing climatic conditions across the



study area for this time period were used to construct the model; these datasets included monthly maximum temperature, monthly precipitation and monthly drought severity. Understanding how fire operates regionally within diverse areas can help increase the understanding of wildland fire at all scales.

## BACKGROUND

Fire does not occur independently of other natural processes; it is highly dependent on suitable conditions in order for ignition to occur and combustion to be sustained. Sufficiently dry fuel in quantities large enough to support the persistence of the fire is essential; these factors are largely dependent on climate. This relationship may initially appear to be fairly straightforward: low precipitation and high temperature dry out fuels. Dry fuels require a lower temperature to ignite compared to moist fuels because less water needs to be evaporated for ignition to occur making ignition much more probable when fuels come in contact with an ignition source (Pyne et al., 1996).

Live fuels respond similarly to dead fuels but on a somewhat longer time scale. Drought conditions can effectively reduce live fuel moisture and convert live fuel to dead fuel as plants struggle to cope with water loss. Moisture in dead fuels fluctuates on monthly and seasonal time scales, suggesting a rapid response to acute hot and dry conditions (Pyne et al., 1996). It is tempting to characterize fire occurrence as a function of prolonged high temperature and low precipitation. The conditions which lead to fire, however, are more nuanced and vary across space (Littell et al., 2009; Westerling et al., 2003). Although the climatic factors associated with fire occurrence have been examined in the Southwest (Holden, Morgan, Crimmins, Steinhorst, & Smith, 2007) and Southern California (Dennison & Moritz, 2009), there is an incomplete understanding of the actual factors leading to increased fire danger, especially in the Interior West.

The Interior West contains a number of unique landscapes. This region incorporates a variety of desert and alpine environments which results in a mix in fire regimes as well. The complexity of the landscape means factors contributing to fire risk are not consistent across the entire region (Littell et al., 2009). More arid regions often do not contain enough fuel to sustain a large persistent fire and fires are often preceded by a moist period to build up sufficient biomass to support fire. On the other hand, alpine regions generally receive more moisture and thus require more severe drought conditions to sufficiently dry out fuels for ignition (Swetnam & Betancourt, 1998; Westerling et al., 2003).

### *Vegetation Response to Drought*

The way local vegetation responds to drought conditions plays an important role in understanding how conditions can potentially lead to wildfire. If an area's native vegetation is adapted to periodic drought, the conditions required to convert live fuels to dead fuels will need to be more severe compared to areas less adapted to such dry conditions (Swetnam & Betancourt, 1998). The way these local environments relate to fuel load is also an important consideration. Arid environments generally support less aboveground biomass compared to areas with higher amounts of precipitation (Evert & Eichhorn, 2004).

Vegetation is inextricably linked to the environment. Unlike animals, individual plants cannot move to cope with unfavorable conditions (Halle, 2002). This suggests plants are reliable indicators of local environmental conditions. Vegetation composition can indicate an area's long-term climate (desert, forest, etc.), while symptoms of plant stress signal more acute environmental conditions (Koppen, 1885; Prentice et al., 1992).

Plants cope with drought in different ways and to different extents. There are two basic ways a plant can manage drought, through either avoidance or resistance. Avoidance is by far the most common tactic which includes minimizing the opening of stomata, water storage in

plant tissues (succulence) and more efficient/extensive root systems. This adaptation to drought allows a plant to maintain normal water potential even as drought severity increases (Simpson, 1981). A truly drought tolerant plant is able to survive reduced water potential, even to the point of being air dry.

Although examples of extreme drought tolerance in angiosperms are rare, its presence among more primitive organisms (algae, lichens, mosses, etc.) is more common. Cryptobiotic soils which occur throughout the Southwest are an example of the extreme drought these organisms can endure. Creosote bush (*Larrea tridentata*), for example, is a flowering plant which also grows throughout the Southwest and can survive after drying out completely. Less extreme examples of drought tolerance include *Sorghum* spp. which maintains a reduced photosynthetic rate when water potential is reduced (Simpson, 1981). Different photosynthetic pathways also play a role in understanding drought conditions as these differences in basic physiology are independent of drought conditions and show that different plant species will lose water at a different rate based solely on photosynthetic pathways.

Phenological differences in vegetation also relate to drought response, particularly in annual grasses like cheatgrass (*Bromus tectorum*). These plants are characterized by short life cycles, sometimes completing multiple generations in a single season (Zouhar, 2003). The fact that these plants die after reproducing regardless of environmental conditions suggests an interesting relationship between the climate and dead fuel loads where conditions which favor plant growth can ultimately lead to a greater amount of dead fuels later in the season.

#### *Climate Relationships to Fire*

The relationships between climate and fire vary across space. Previous research has examined relationships between area burned and climate conditions using different spatial scales throughout the Western U.S. (e.g., ecoprovinces and grid cells). These studies found

positive relationships with prior year precipitation and negative relationships with drought conditions and area burned in locations generally dominated by fine fuel types (e.g., grasses), while areas containing heavier fuels (e.g., forests) were positively associated with drought conditions during the fire season (Littell et al., 2009, Westerling et al., 2003). Precipitation has also been associated with high frequency changes in fuel moisture which affects fire conditions during the fire season (Trouet et al., 2010). Fine fuel moisture is generally more affected by these high frequency fluctuations in precipitation than heavier fuels (Westerling et al., 2003).

Spring temperatures, and thus timing of snowmelt, are also climatic factors affecting wildfires across the Western United States. Warmer spring temperatures tend to bring on a higher amount of drought during midsummer (Westerling, Hidalgo, Cayan, & Swetnam, 2006). This not only suggests that particular regions are affected by environmental conditions differently, but also emphasizes the importance of antecedent conditions at least one year prior.

Various methods of spatial aggregation have been used to examine relationships between climate variables and fire occurrence. Westerling et al. (2003) used 1° grids as a way of maintaining homogenous fuel types; however, the authors note that with grid cells this large the topographic variability in mountainous regions may still contain a variety of fuel types. Entire ecoprovinces have also been studied to isolate different climate and land cover types throughout the region (Littell et al., 2009). Aggregation has also been done temporally by analyzing annual fire patterns in terms of total area burned (Littell et al., 2009; Trouet et al., 2010) or monthly counts of fires started within a grid cell (Westerling et al., 2003).

Westerling et al. (2006) addressed the notion that land use change may play a role in the increase of area burned by wildfires seen over the past decades. It was shown that even areas which have seen little-to-no land use change since the mid-1980s have experienced this increase in area burned—particularly in the Rocky Mountains. Even though Westerling et al.

(2006) examined this question in terms of the entire Western U.S. and management may play a larger role at finer spatial scales, it seems reasonable to expect the conditions driving fire occurrence is most strongly influenced by climate variables, rather than land use.

In addition to climatic relationships to fire occurrence, climate's ties to fire severity has also been examined. Burn severity is somewhat of a fuzzy term within the wildland fire community (Keeley, 2009). First, severity is not universally defined for wildfire. Keeley (2009) distinguished between the varying definitions by drawing lines between fire intensity, fire severity and burn severity. Additionally, there is another term proposed, ecosystem response, which addresses the broader consequences of fire on natural systems. All of these terms are meant to occupy a specific area in the continuum of fire effects. On the immediate time scale, fire intensity describes the amount of energy released from the fire's front, while fire severity addresses mainly the loss of biomass postfire. Burn severity is often used interchangeably with fire severity. Keeley (2006) distinguishes burn severity as incorporating both fire intensity and ecosystem recovery using field-based metrics such as the composite burn index (CBI).

Remote sensing is often used to assess fire severity and was used for this study. The commonly used differenced normalized burn ratio assesses postfire biomass loss (Escuin, Navarro, & Fernandez, 2008). This algorithm, although highly correlated with fire severity, is sometimes a poor predictor of ecosystem response due to the range of trajectories different locations take after a fire. Factors such as resprouting and plant cover are not well captured by the dNBR algorithm (Keeley, 2009). It is beyond the scope of this study to examine the question of defining burn severity further, but it is worth acknowledging that confusion exists regarding measures of burn severity and how these measures relate to broader ecological effects.

There are remotely sensed measures of fire severity which more closely agree with field assessments of burn severity, such as the RdNBR algorithm (Miller et al., 2009). Dillon et al.

(2011) conducted an investigation into the relationship between various environmental factors and their effect on burn severity in the northwestern and southwestern United States. The RdNBR algorithm was used as the measure of burn severity and modeled using random forest (Breiman, 1999). The study found topography to be most important factor in determining how severely a location burns as assessed by RdNBR. Climate played some role, but this study suggests that the processes which drive severity may be more local as opposed to broader climate patterns which have been shown to drive overall fire occurrence and area burned (Westerling et al., 2003; Littell et al., 2009).

## METHODS

### *Study Area*

The location of the study area was delineated using hydrologic unit codes (HUC) developed by the USGS (Seaber, Kapinos, & Knapp, 1987) and incorporates the Great Basin (HUC 16) and the Upper Colorado River Basin (HUC 14). These two watersheds are similar climatically and encompass much of the Interior West. The use of watersheds to define the study area helps ensure that the inputs from the climate variables, particularly precipitation, are self-contained hydrologically as well as making boundaries simpler in terms of management. This area covers approximately 662,000km<sup>2</sup> (Figure 1). The region contains a diverse collection of ecosystems which range from high elevation deserts to alpine wetlands. The landscapes within the study area are fairly representative of those seen throughout the Interior West.

### *Climate Data*

Multiple datasets were used to examine climate-fire interactions across the study area from 1984-2009. Parameter-elevation regressions on independent slopes model (PRISM) dataset (PRISM Climate Group, 2010) consists of continuous gridded temperature and precipitation data interpolated from weather stations for each month across the United States at a spatial resolution of 2.5min (≈4km). The spatial interpolation of the climate data also accounts for the effect elevation has on the various climate factors (Daly et al., 2000). Elevation is represented by a digital elevation model (DEM) during the interpolation. These data provide the initial climate data for the study which includes: maximum temperature, minimum



temperature and precipitation. This dataset is used extensively for short term regional scale climate studies in the United States (PRISM Climate Group, 2010).

Another product derived from the PRISM dataset in conjunction with the variable infiltration capacity model (VIC) is the self-calibrated Palmer's drought severity index (SCPDSI) created and distributed by the Western Regional Climate Center (Wells, Goddard, & Hayes, 2004). The VIC model is another gridded dataset which is used to provide information related to hydrological processes such as soil infiltration and topography. This model is combined with climate data to calculate drought severity.

The SCPDSI measure represents a location's water balance compared to that location's historical normal; if the measure is negative the location is at a water deficit while a positive value represents a water surplus relative to the past neutral water balance of that location. This measure is based on the traditional Palmer's drought severity index (Palmer, 1965) except the constants used to calculate the index are calibrated for each location as opposed to the regionally-derived constants used in the original index. This makes the index more robust and allows for direct comparisons between sites, something that is problematic with the original PDSI since the constants used to determine the water balance are not based on local measurements but instead are calculated and applied regionally. The arid West is complex and varied so calculating the index based on constants which apply to the entire region may not reflect local climate, limiting the index's comparability (Wells et al., 2004).

#### *Fire Data*

Fire occurrence and severity was represented by the Monitoring Trends and Burn Severity (MTBS) product distributed by the Remote Sensing Applications Center (USFS). This dataset represents the spatial extent and fire severity of all large fires (>1,000 acres) from 1984 to 2009 at a spatial resolution of 30 meters. There were a total of 1,433 large fires used in this

study with an average of 55 fires occurring per year (Figure 2). During this period a maximum of 142 large fires occurred in 2006 and a minimum of 9 large fires occurred in 1990.

The burn perimeter and severity information for these fires was derived using the differenced normalized burn ratio (dNBR) algorithm (Eidenshink et al., 2007). The dNBR identifies burned areas using Landsat Thematic Mapper (TM) satellite imagery by identifying the relationship between the near infrared (Band 4) and shortwave infrared (Band 7) image bands using the equation:

$$NBR = \frac{(B4-B7)}{(B4+B7)}.$$

This value is calculated for two images, representing prefire and postfire. The two NBR images are differenced to indicate severity of a fire (Lentile et al., 2006).

The dNBR fire severity measure is highly dependent on the original land cover prior to the fire since the largest possible difference, and thus the maximum severity for a location is a function of the prefire NBR which is highly correlated to biomass (Miller et al., 2009; Eidenshink et al., 2007). Areas with low prefire biomass will generally record a lower severity compared to a similar location with higher biomass. Eidenshink et al. (2007) defines the severity measurement in the MTBS dataset consistent with NWGC (2005), which defines fire severity as, “Degree to which a site has been altered or disrupted by fire; loosely, a product of fire intensity and residence time” (p. 75).

Land cover was also accounted for in various aspects of the study. The 2006 National Land Cover Dataset (NCLD) was used as a static indication of vegetation types present throughout the study area. The NCLD is produced by classifying Landsat TM imagery acquired during 2006 based on the spectral patterns for each location. Each land cover type has a specific spectral pattern which is used to determine the land cover present within each pixel (Homer,

Fry, & Barnes , 2012). Although this dataset only provides a snapshot of land cover at a specific point in time, it does provide some indication of a location's characteristic vegetation, which is sufficient for the purposes of this study.

### *Data Processing*

The raw values from each PRISM dataset were transformed to represent standardized anomalies, which are essentially z-scores of climate variables. Pixel-wise anomalies were calculated for each month in the study period to remove the effects of spatial and seasonal variation in raw values. These standardized values can be directly compared across datasets and between months allowing the different variables and fires to be analyzed together.

Precipitation required an additional log transformation prior to anomaly calculation. Precipitation data often have to be transformed to correct their generally skewed distribution caused by the values being bounded by zero (no negative precipitation) and a small number of very large values. This log transformation increased the options available for further statistical analysis since the transformed dataset's distribution is now approximately normal.

The values of each variable raster were extracted from each fire location into a table. Some larger fires encompassed multiple 2.5min PRISM pixels, which resulted in an individual fire occupying more than one row in the table. The pixels of these larger fires were averaged, yielding one value for each variable per fire. The final table contained one set of values for each fire, giving each fire equal weight. This prevented larger fires with multiple data entries from being overrepresented during data analysis.

A variation of superposed epoch analysis (SEA) (Trouet et al., 2009) was used to generate a new dataset from this table. The climate values from each fire were extracted from a time period spanning 24 months prior to the date of the fire. This created a cohesive dataset of antecedent climate before each fire in which the first column represents the climate variable 24

months before the start month of a fire; subsequent columns lead up to the month in which the fire actually started. This allowed for the comparison of the fire associated time series as well as with time series which did not end in fire. This lagged dataset was the primary data used for subsequent analysis.

Fire severity was also extracted from each fire in terms of percent low, moderate and high severity. These classes are determined by an analyst-defined threshold applied to the raw dNBR output. Although there are other severity classes represented in the MTBS dataset, only these three severity classes were considered since the other classes refer to either undefined or unburned pixels. The proportional severity values were converted into a single continuous value using the equation:

$$Severity = 3(\%High) + 2(\%Moderate) + 1(\%Low)$$

This continuous variable was scaled in various ways to make the severity values more interpretable. First, the  $\log_{10}$  of the raw severity values were taken and then scaled between 0 and 1. This measure of severity represents the relative severity of individual fires within the study area.

Monte Carlo sampling was used to extract a random set of 24-month time series across the study period in order to assess if and when the median of the fire-associated time series differed from a random collection of time series. A random time series was extracted from each fire location, these time series were assembled and the median value was taken. This sampling was done 1,000 times and a 95% confidence interval was constructed to assess each variable's departure from random. It was shown that at around a 6 month lag both prefire precipitation and maximum temperature deviated from the confidence interval generated by the random sampling. Prefire drought severity had a longer significant lag of 24 months.

Time series clustering was done using a hard competitive learning method of clustering; this method is similar to K-means clustering except the initialization of the centers is not entirely random. This method has been shown to be more robust in datasets which have varying densities within them and prevents the common issue of centers falling into “local minimums” (Fritzke, 1997). The Calinski criterion, developed by Calinski and Harabasz (1974) to optimize cluster partitioning, was used to determine the appropriate number of clusters for the data. This index determines the optimum number of partitions to be the number which minimizes within and maximizes between group variance. This approach identified five groups based on specific patterns in climate anomalies preceding fire occurrence.

Since the dNBR algorithm used to calculate fire severity is very dependent on land cover (Miller et al., 2009) an effort was made to incorporate vegetation type into the severity model. The proportions of six land cover classes were extracted from the 2006 National Land Cover Dataset (NCLD) for each fire (Homer et al., 2012) in a similar fashion as was done with the fire severity values. The six land cover classes were Barren Land (Class 32), Deciduous Forest (Class 41), Evergreen Forest (Class 42), Mixed Forest (Class 43), Shrub (Class 52) and Grassland (Class 71).

The values from this dataset represent a static picture of land cover at each location in 2006, not the land cover present during the time of the fire. Over time land cover can change in a particular area, but these data are still able to give some indication of the land cover present within each fire perimeter during 2006. K-means was used to assign each fire into a land cover cluster based on the proportional land cover measures. Ultimately the data were divided into three groups. Although three groups were not determined as the most optimal number according to the Calinski criterion, which was eight, it was a manageable number which produced clear and distinct groups of land cover.

For fire risk predictions, rasters of each variable were created for the prediction month. Euclidean distances were calculated for each pixel within the extent of the prediction rasters based on the distance from a pixel's climate pattern to the cluster centers generated during time series clustering, each pixel is assigned to the class with the shortest overall distance. From this, two rasters were created, one representing the cluster assigned to each pixel and another with the distance from the closest cluster center to the pixel (Figure 3). These distances were analyzed for the fires which were used to create the cluster centers and quantiles were determined. This gives an idea of how closely the climate pattern of a pixel matches the climate of its assigned cluster center, and can be used to give a quick assessment of prediction uncertainty.

### *Modeling*

The ultimate goal of this study was to develop a model capable of predicting fire risk based on climate patterns from previous months. Maximum entropy (Phillips, Anderson, & Schapire, 2006) was chosen because of the way this technique applies to modeling fire risk. The input data used were time series of maximum temperature, precipitation and drought severity in the months leading up to the start of a particular fire.

Maximum entropy (MaxEnt) has been used extensively in ecological research and has multiple advantages over more traditional modeling methods: (1) MaxEnt is designed to work with presence-only data, which offers an intuitive approach to modeling fire. Since fires do not occur in all places where fire-prone conditions exist, it is difficult to define a true absence. MaxEnt does not treat background values where fire has not been observed as absences during the modeling process. (2) Probabilities are generated for predicted areas which make for more nuanced interpretation as opposed to a binary presence/absence prediction, and avoid the need to choose arbitrary thresholds. (3) Environmental data from across the study area are used to

characterize the environment, instead of simply using conditions at presence sites (Phillips et al., 2006).

Separate models were created for each cluster and predictions were made for 10 separate months to assess the model's predictions during different periods. The models were run 100 times for each month and validated by leaving out a random 25% of the data for testing. The variables for each model included 6 months of antecedent precipitation and maximum temperature, 24 months of antecedent drought severity, and the raw value of maximum temperature at lag 0. This raw maximum temperature value was included as a way to inform the model about the season being modeled, since all of the other variables have been converted to anomalies which removed seasonality from the dataset. This prevented dry winters being predicted as having high fire risk.

The raw probability values from each model are not directly comparable to other models. The variation in the probability values between models is partly due to varying model performance in addition to the characteristics of the group being modeled (Phillips, et al., 2006). Thresholds provide a way to assign common values to different models since the definitions of the thresholds remain constant even though the actual values change from model to model. Classes of fire risk were determined by these thresholds which were calculated in the model outputs. In ecology, these thresholds represent different cutoffs for determining whether or not the predicted value for a pixel should be considered a species presence or absence. In this study three different thresholds were used to represent the level of fire risk for a pixel during the month being modeled. Table 1 shows the four classes derived from these thresholds with a brief description of the threshold calculation.

A confidence interval was calculated for each pixel by creating a probability distribution function based on the 100 model runs. The probability distribution of predicted values was

compared to the thresholds associated with the fire risk classes. The highest fire risk category whose threshold value was below the 95<sup>th</sup> percentile of the distribution was assigned to the pixel. The final classification was created by taking the predicted risk class from the pixel's assigned cluster (Figure 4).

Fire severity was modeled with a random forest (Breiman, 1999) using the continuous severity variable as the response. The data used to construct the tree were the same used in the fire risk models except the time series clusters were replaced by the land cover clusters and the raw maximum temperature variable was replaced by elevation values derived from the same DEM used to produce the PRISM climate data. Random forest takes an iterative approach to regression trees (Breiman, Friedman, Stone, & Olshen, 1984) where multiple trees are created using a random selection of training samples and input variables.

Separate random forest models consisting of 1,000 individual trees were generated for each of the three land cover clusters. Predictions were then made from the models across the entire study area using climate data from July 2012. Each pixel within the study area was assigned to one of the three land cover clusters and then predicted using the corresponding random forest model



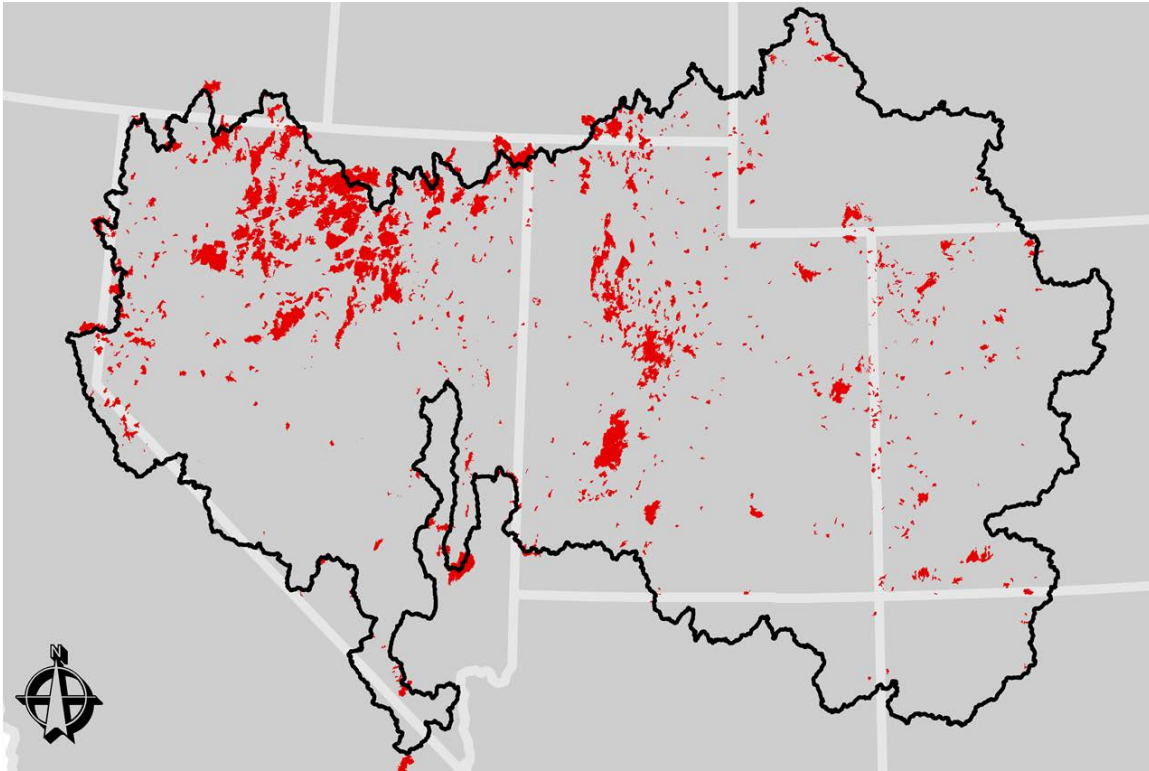


Figure 1. Study location. Red polygons represent the fire perimeters used in the study.

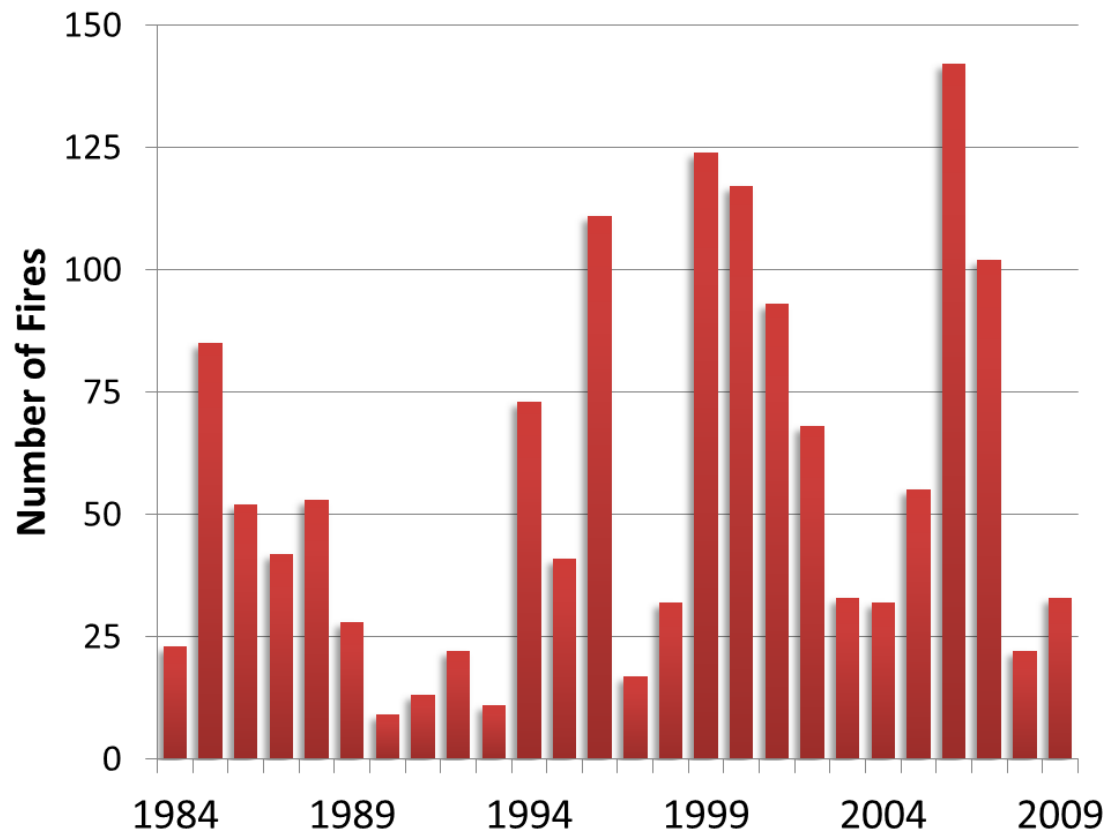


Figure 2. Annual number of large fires that occurred during the study period.

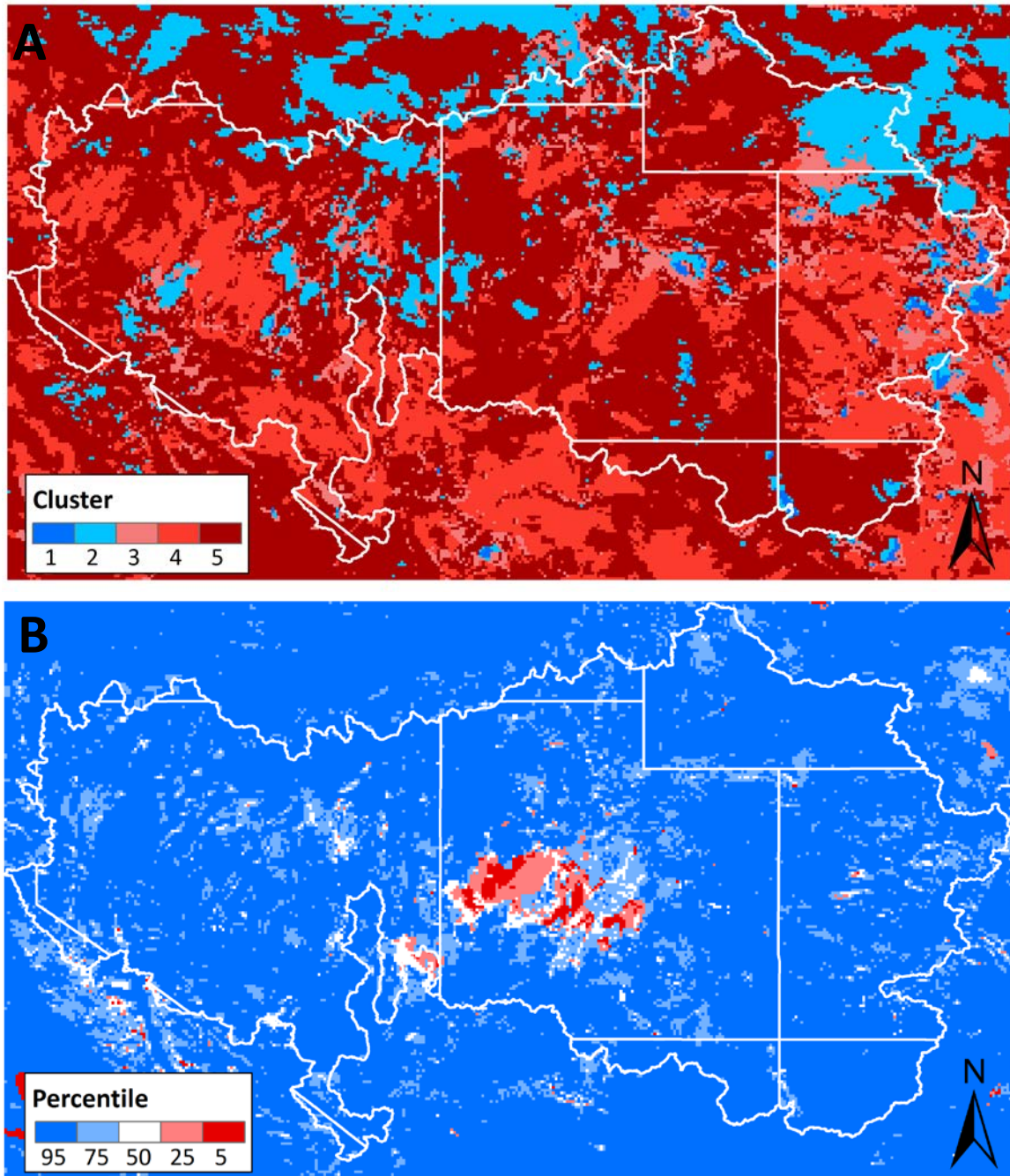


Figure 3. Calculations made for August 2011. (A) Cluster assignments based on the cluster center with the smallest Euclidean distance to each pixel. (B) Distances from each pixel to the closest cluster center. Percentiles were calculated from the distances of the training fires to their respective cluster centers.

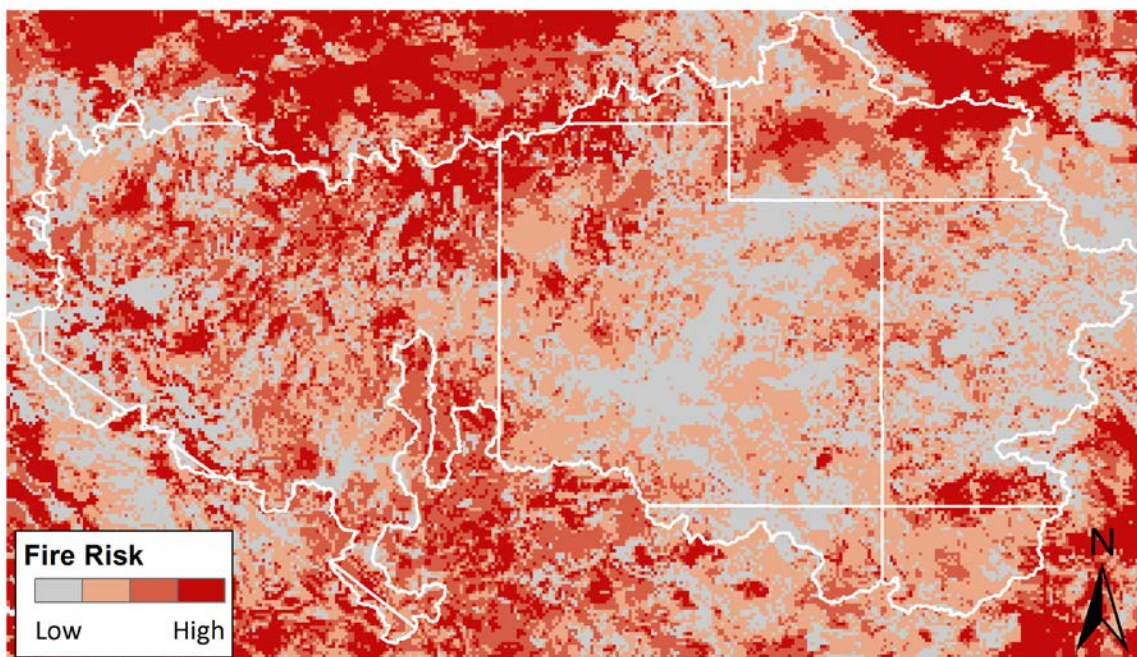


Figure 4. Classified model prediction for August 2011. Fire risk categories were based on thresholds generated in the model output. These classified results represent a conservative estimate (i.e., fire risk may be overstated) since each pixel's classification was determined with a 95% confidence.

Table 1

Description of thresholds used to determine fire risk classes

Fire Risk Class	Threshold	Threshold Description
Very Low	< Minimum Training Presence	Predicted value was less than any training fire's predicted value.
Low	Minimum Training Presence	Predicted value was at least the minimum value predicted for a training fire.
Moderate	Equal	A value which balances commission error (false negative) with omission error (false positive) for the training fires.
High	5 <sup>th</sup> Percentile Training	Predicted value was in the 5 <sup>th</sup> percentile of training fire predicted values.

## RESULTS

The time series clustering revealed five distinct climate patterns present in the months prior to fire (Figure 5). These five groups are more generally characterized by patterns in which fires were preceded by predominately wet or predominantly dry conditions. What further separates these groups is mostly the magnitude and/or the timing of these wet/dry periods.

An exploration into the land cover composition for each cluster was done using the 2006 National Land Cover Dataset (Homer et al., 2012). The land cover composition of the clusters agrees with this hypothesis. The “wet” clusters (1 & 2) were at significantly lower elevations, 1,768m on average, and were composed of significantly more shrubland compared to the midelevation (1,930m) clusters (3 & 5) which had fairly variable compositions. Cluster 5 had much more shrubland and Cluster 3 had more evergreen forest. The highest elevation (2,034m) cluster (4) exhibited the most severe drought and was predominantly composed of conifer forest (Figure 6).

These clusters are often distributed within the same year, and are not merely products of dominant annual conditions over the study region. There is, however, a clear pattern of increased “wet” fires interspersed among the fairly consistent “dry” fires (Figure 7). These results reinforce that dry conditions often lead to fire, but wetter than normal conditions can also create fire conditions under certain circumstances. Antecedent wet clusters also had a larger average area burned compared to the antecedent dry clusters (Figure 8).

The MaxEnt models identified areas with similar climate patterns to those which have resulted in fire in the past. To assess the goodness-of-fit for these models the area under curve



(AUC) score was used. The AUC score reflects the ability of model to discriminate between the group being tested (climate patterns associated with fire) and the other data. An AUC of 0.5 means the model does no better than random at distinguishing the test group from the rest of the data. As the AUC increases the model's ability to separate the two groups is improved. A test dataset from 2010 was modeled with a high average AUC score of 0.945. However, only clusters 2, 4 and 5 were present during 2010 and only 26 fires occurred during this year – barely above the 25<sup>th</sup> percentile for the study period.

Another assessment of model performance was undertaken by comparing the classified model output from June 2007 with actual fires which occurred during the month. The classification results showed 50% of observed fire locations classified as having a high risk and 83% of the locations were classified as either moderate or high (Figure 9).

The inclusion of the raw maximum temperature variable worked well for determining the season which is being predicted and the likelihood of fire occurring during that season. The model was run for 3 winter months (January 2010, December 2011 and January 2012) in order to determine the performance of the raw maximum temperature variable. The results from these winter months show that the inclusion of this variable prevents fire from being predicted during cold months (Figure 10).

The clusters based on land cover showed three distinct, dominant vegetation types within the study fires. Cluster 1 contained 291 fires and was dominated by shrub and grassland, Cluster 2 (877) by shrub and Cluster 3 (257) by evergreen forest. These clusters were also distinguished by elevation as well; shrub/grassland areas were at lower elevations, shrub dominated locations occupied midelevations and forested locations were seen at higher elevations (Figure 11).

The random forest models provided some insight into factors contributing to fire severity within the study region. In terms of variable importance, elevation was by far the most important predictor of fire severity for both the shrub/grassland and shrub land cover clusters based on the change in mean squared error when that variable was excluded during the construction of a particular tree. Although elevation is a simple, static variable it could act as a proxy for more complicated variables (i.e., topography, land cover, climate, etc.). The forest land cover cluster, however, showed drought severity during the previous growing season as the most important predictor.

The predictive power of the random forest models were assessed in a number of ways. Part of the modeling process involved excluding a random selection of samples during the construction of each tree. The resulting tree was then used to predict values for the samples, which were left out. The predictions were aggregated and then compared to the actual value for each sample, allowing for a measure of prediction accuracy within the model. Root mean squared error (RMSE) was used to measure this prediction accuracy by comparing the actual value of the sample to the aggregated prediction created during model construction. The calculated RMSE for all models was 0.2124, and was fairly consistent between the different models.

The predictions made for July 2012 illustrate elevation's dominance in the random forest models (Figure 12). High elevation areas are consistently predicted as high severity while low elevations are predicted as low. The correlation between elevation and fire severity is likely related to the dNBR measure of fire severity, which still appears to be dependent on land cover even when land cover is partially controlled for by the land cover clusters.

The uncertainty around the predictions was also assessed. The variation within the 1,000 predictions made for each location was calculated using the interquartile range (Figure

13). There was spatial variation in the ranges throughout the study area. Closer examination revealed that the highest variation tended to occur in midelevation areas. Elevation is a very important variable in the models, since regression trees split data using discrete values areas which are at elevations that are neither high nor low and would be expected to produce highly variable predictions. It is also possible that most of the fires occurred in these midelevation areas. The midelevation land cover cluster (Cluster 2) was comprised of 877 fires. The large number of fires in these areas also means there would likely be more variability among the fires in this cluster compared to the other clusters with fewer fires.



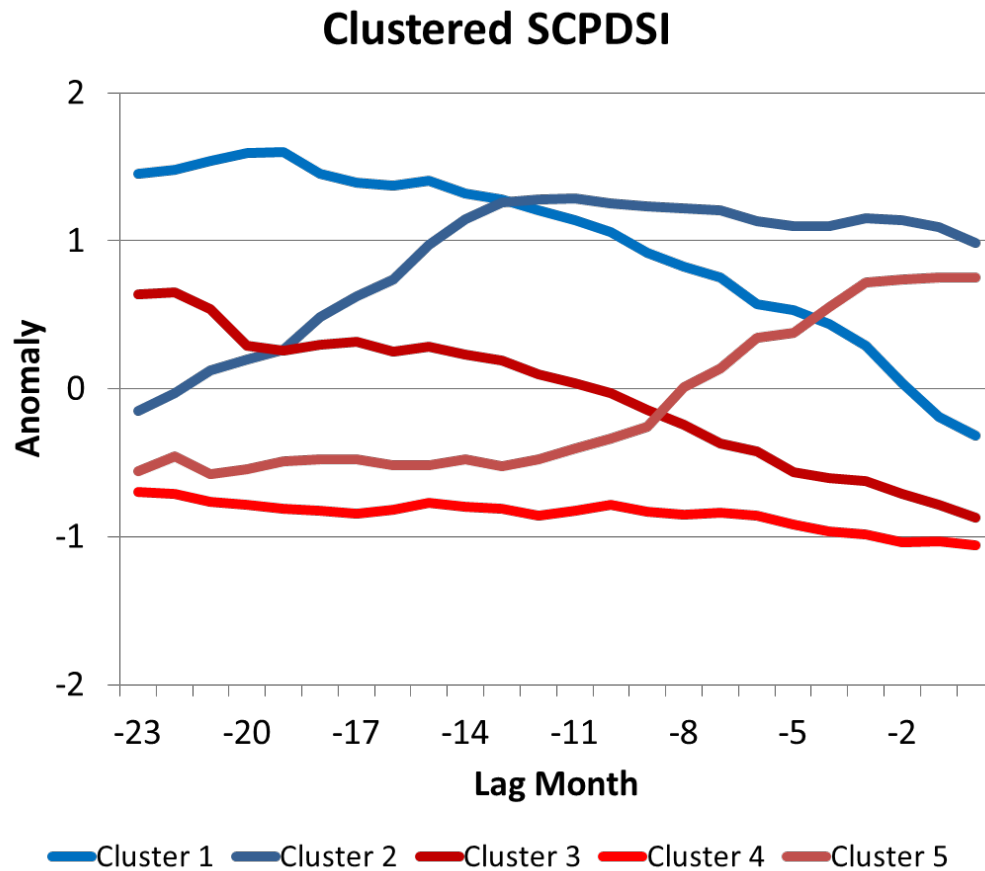


Figure 5. Cluster centers for drought severity (SCPDSI). Blues lines denote fires in which conditions preceding fire are characterized by generally wetter than normal while red lines are associated with preceded conditions which are drier than normal.

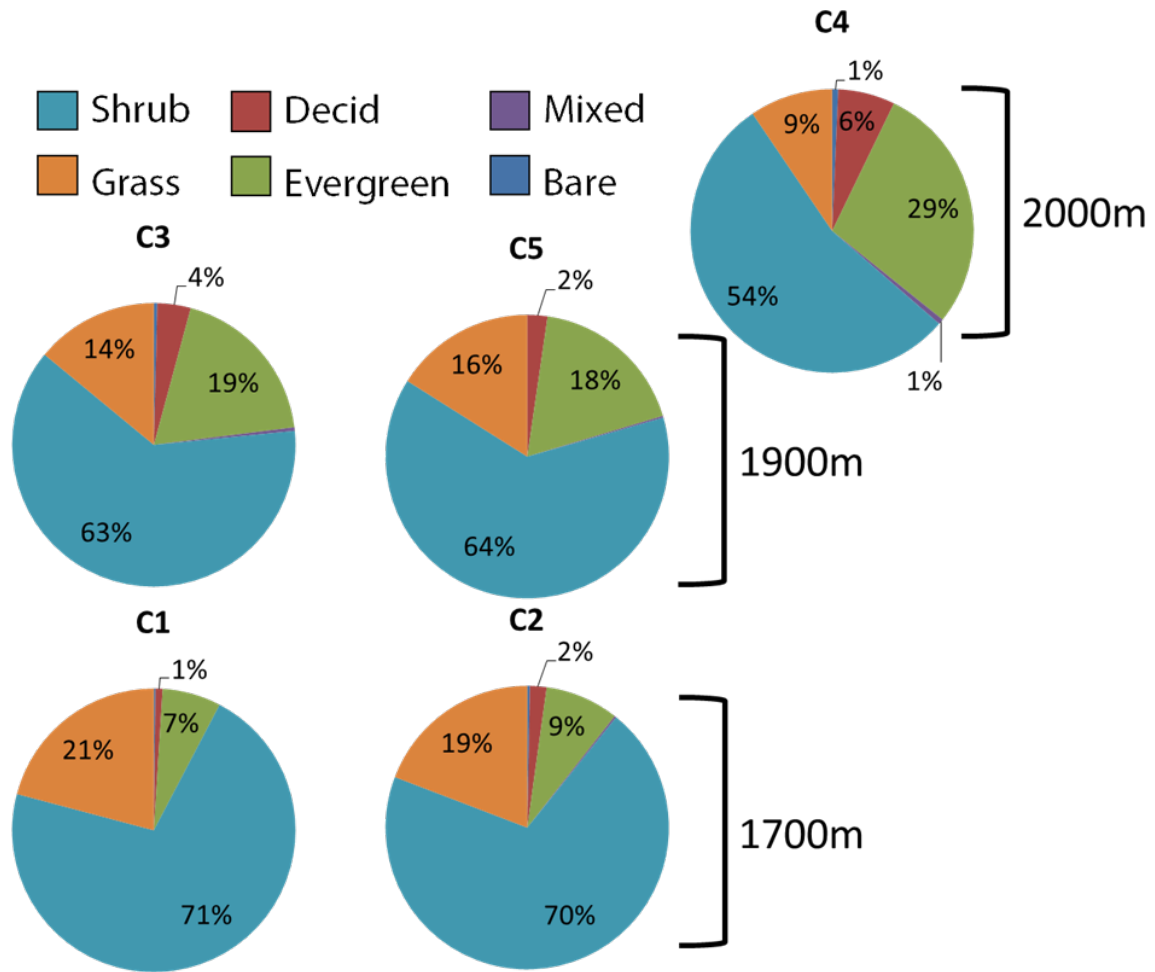


Figure 6. Land cover and average elevation of clusters

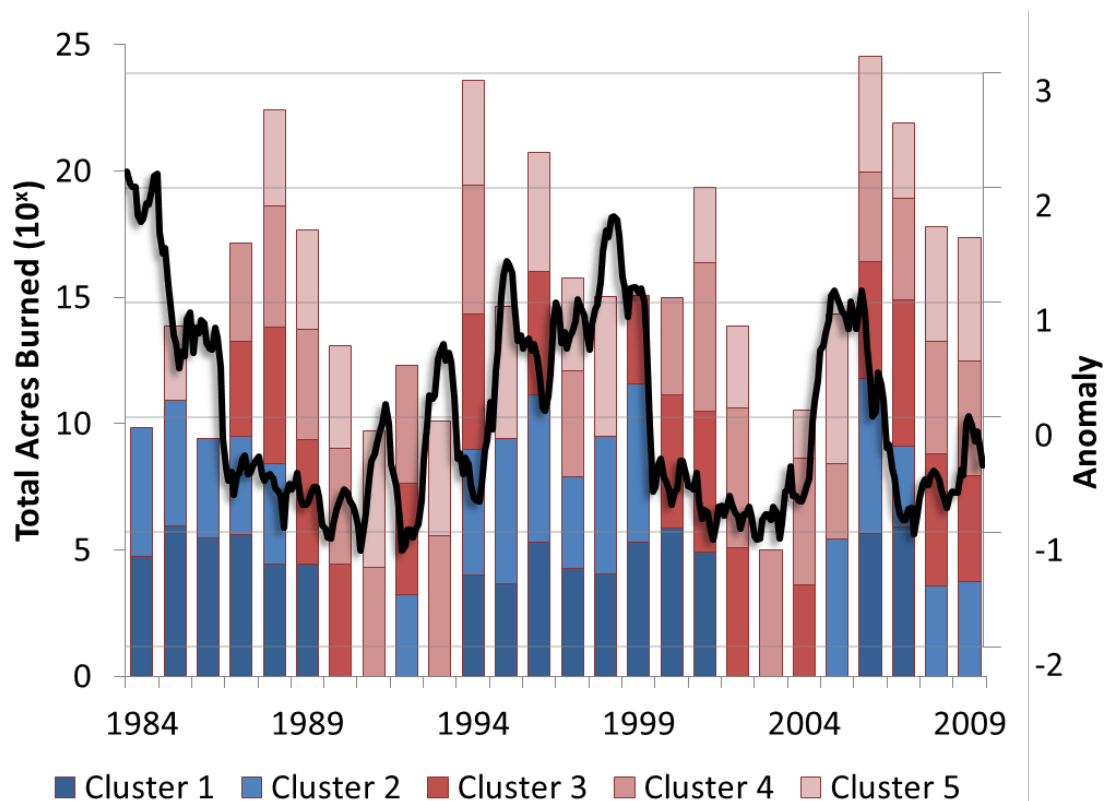


Figure 7. Area burned per year by each cluster. Drought severity (SCPDSI) is overlaid to show how area burned is associated with fluctuations in drought severity. Fires preceded by anomalously dry conditions (red bars) remain relatively constant, while fires preceded by anomalously wet conditions (blue bars) appear during and after periods of anomalously high SCPDSI (low drought severity).

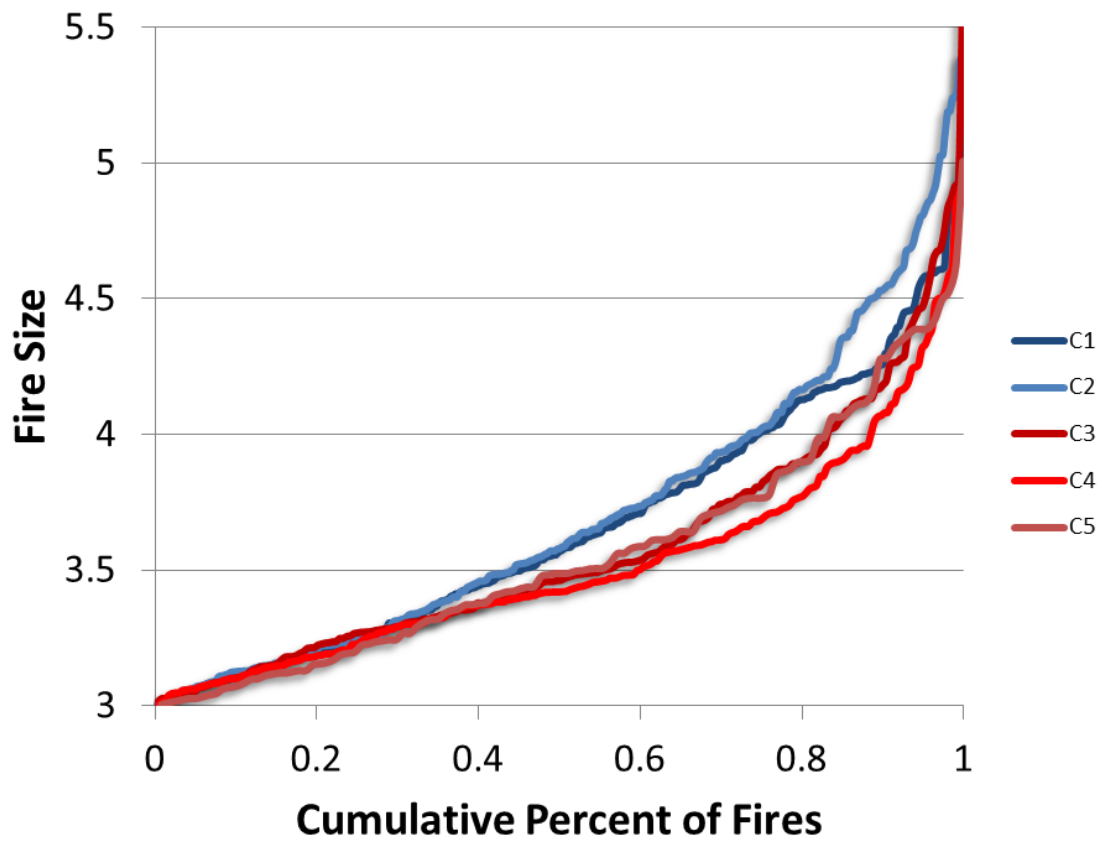


Figure 8. Comparison of fire sizes between clusters. Blue lines are associated with clusters characterized by antecedent wet conditions, while red lines are associated with antecedent dry clusters. Fire size is calculated as the log of the fire size in acres.

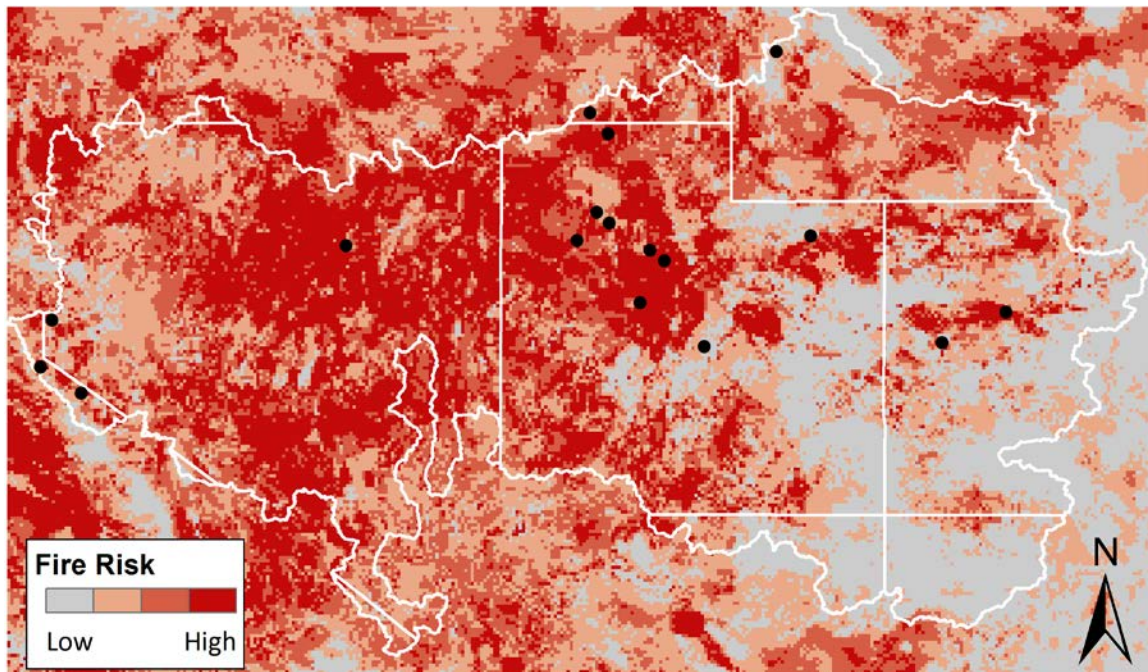


Figure 9. Classified output from model prediction for June 2006. Black points represent actual fires from this month, 50% of the points fall within a high risk pixel and 83% fall within either moderate or high risk pixels.

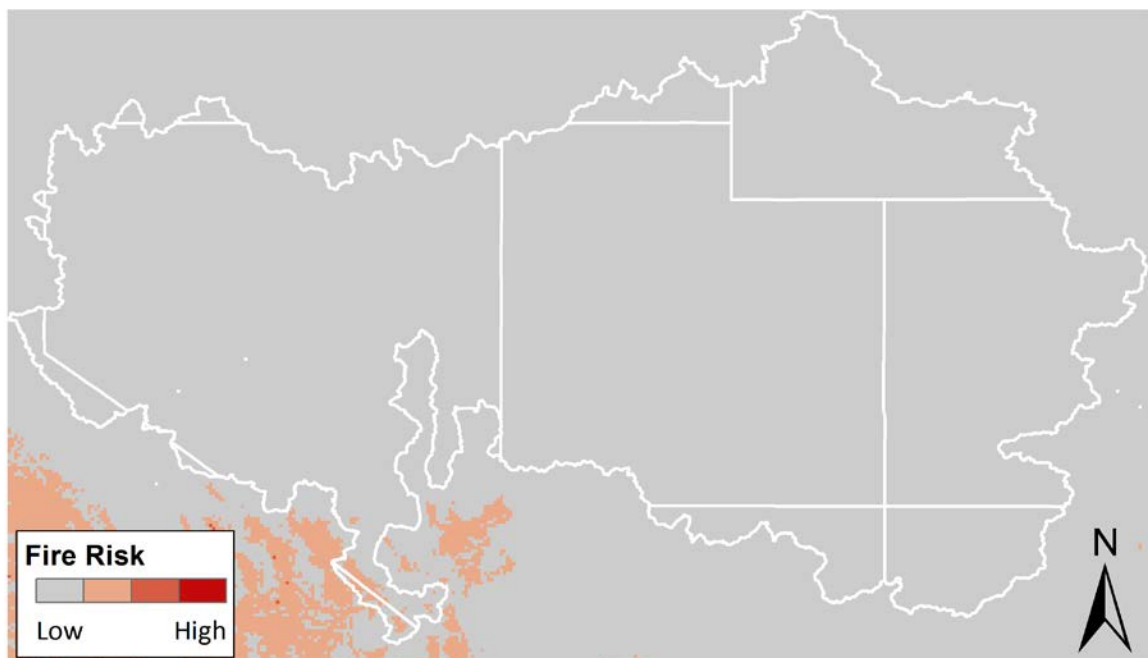


Figure 10. Classified output from model prediction for January 2012. Fire risk is low throughout the study area due to the inclusion of a raw maximum temperature value for the month of the prediction. The inclusion of this variable prevents the prediction of high fire risk during dry winters, when a prediction based solely on anomalies would indicate higher fire risks.

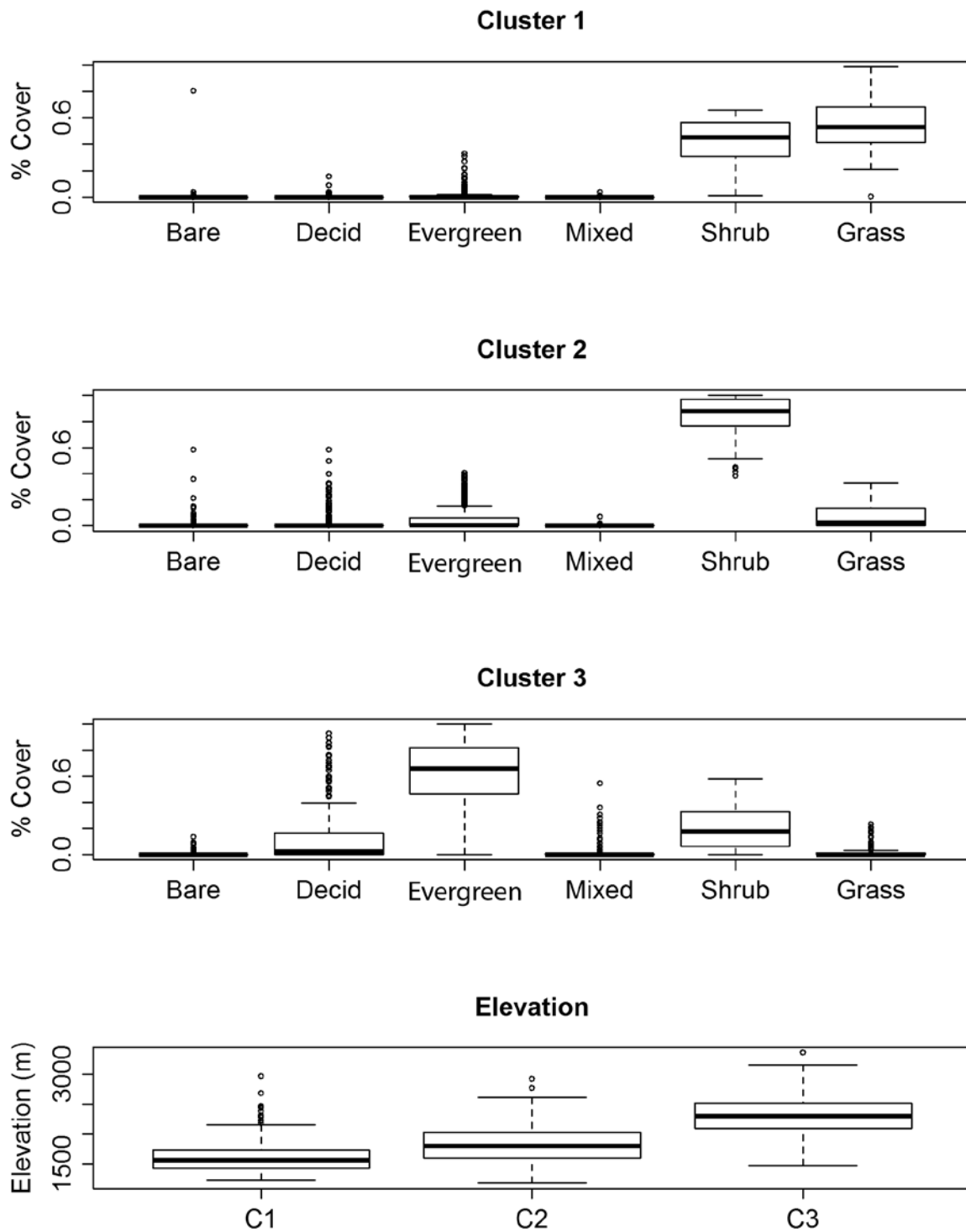


Figure 11. Composition of land cover clusters. Cluster 1 is dominated by shrub and grassland and occupies lower elevations. Cluster 2 is mostly shrub and generally midelevation. Cluster 3 is the highest elevation and composed of evergreen forest.



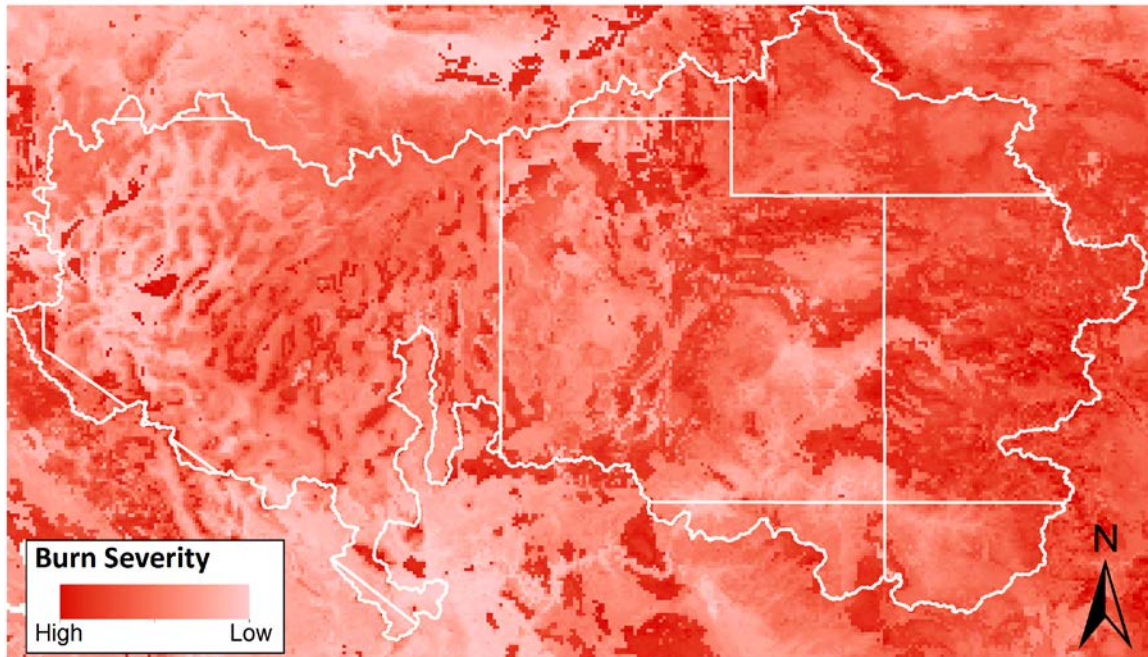


Figure 12. Burn severity predictions from random forest models for July 2012. Severity predictions are largely determined by an area's elevation. High severity predictions are also located at high elevations, while low severity predictions are found at lower elevations.

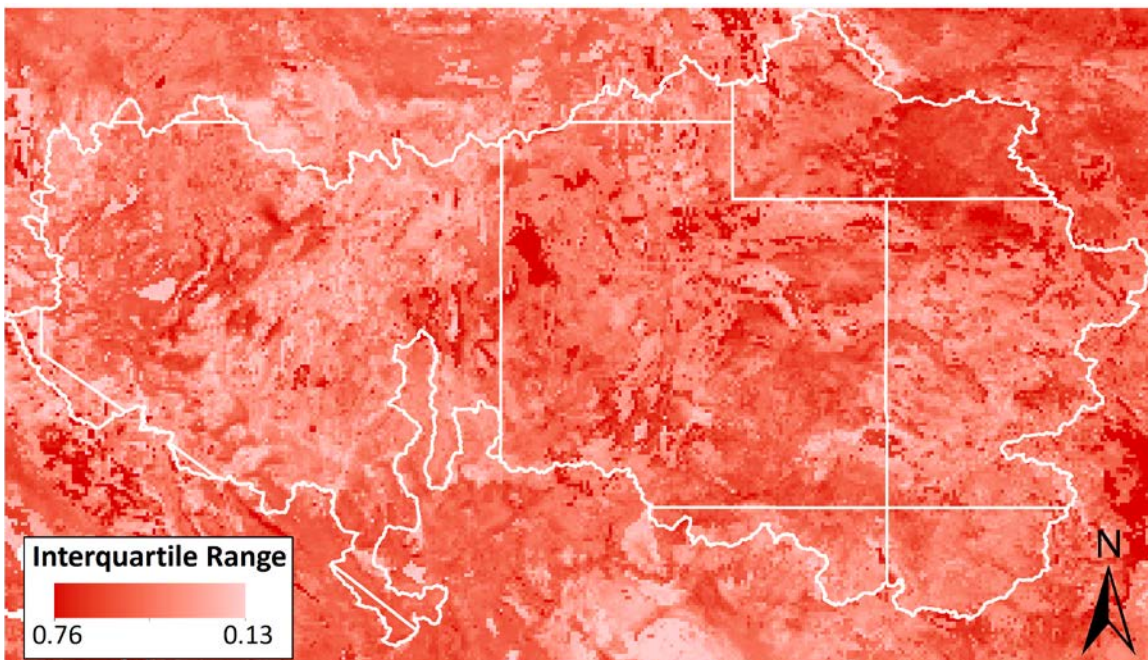


Figure 13. Interquartile range of 1,000 predictions generated by the random forest models for July 2012. The most variable predictions (dark red) occur mostly in midelevation areas. The high variation in these areas may be due to the model's reliance on elevation as the primary predictor of severity. Midelevations may be ambiguous if they lie close to a split in the regression tree. The large number of fires which occurred at midelevations may also contribute to the large amount of prediction variability at these locations.

## DISCUSSION

Although the fire severity models were not as powerful compared to those developed by Dillon et al. (2011), analysis of variable importance yielded some insight into the environmental factors associated with fire severity. The use of the RdNBR algorithm and more complex topographic variables appear to improve model performance compared to using the dNBR algorithm and elevation. As previously mentioned, improved performance achieved using the RdNBR algorithm is most likely due to high correlation between prefire biomass and the dNBR-derived severity classification (Miller et al., 2009). Local topographic factors (slope, aspect, complexity, etc.) play an important role in fire intensity which ultimately relates to fire severity (NWCG, 2005; Pyne et al., 1996); these factors are simply not captured by elevation alone. The use of the RdNBR algorithm as the measure of fire severity along with the inclusion of detailed topographic variables would be expected to improve subsequent investigations into the environmental drivers of fire severity within the Interior West.

The climate time series clusters support observations made in previous studies (Littell et al., 2009; Westerling et al., 2003; Whitlock, Higuera, McWethy, & Briles, 2010) that attributed the relationship between antecedent dry versus antecedent wet fires to climate-limited versus fuel-limited fire regimes. The differences between these two regimes are generally characterized by antecedent wet conditions, which increase fuel loads in fuel-limited areas, and antecedent dry conditions affecting fuel moisture in climate-limited locations (Westerling et al., 2003).



This idea of climate-limited versus fuel-limited regimes being the main process behind the climate patterns is reinforced when the average land cover composition and elevation are compared between the clusters. The average land cover and elevation of clusters 3, 4 and 5 are most consistent with a climate-limited regime, meaning that fuel is always abundant enough to support a large wildfire, but the average climate in these areas does not often support the conditioning of fuels required for fire. In the Interior West these areas would most often be higher elevation locations which generally receive more precipitation and are dominated mostly by forest when compared to the lower elevation grass and shrubland. Fuel-limited regimes are areas in which climatic conditions are frequently sufficient for fuel conditioning but these climates are also characterized by sparse vegetation meaning the fuel load is insufficient to support a large fire. An antecedent wet period increases the fine fuel biomass and connectivity in these areas, and higher fuel loads are readily dried out when conditions return to normal. These locations are generally covered by sparse distributions of grass and shrub.

The differences in fire size between clusters may also link to fuel type. Larger amounts of fine fuels, resulting from antecedent wet conditions, burn much more quickly compared to heavier fuels (Westerling et al., 2003). A predominantly fine fuel fire would tend to spread more quickly, consuming a large area before the fire is contained.

The topography of these areas may also contribute to the differences in fire size. Within the study area lower elevation locations are often less complex topographically compared to higher elevations. Complex topography effectively impedes fire spread due to variations in wind direction and physical barriers (e.g., riparian areas, steep slopes, etc.). The slowing of fire spread may, however, result in an increase in fire severity as the fire burns longer in a particular location (Pyne et al., 1996).

As the climate continues to shift, the patterns currently associated with fire provide insight into the potential changes in fire regime which can be expected in response to the changing climate. Projections for the Western United States describe increasing drought throughout the region (Gutzler & Robbins, 2011). If current projections are correct the resulting effect on fire occurrence may not be as simple as just more fire. Increasing drought may result in more dry fires (clusters 3, 4 and 5) which tend to occur at higher elevations in locations with abundant heavy fuels. However, drought may also reduce the amount of lower elevation grass fires as biomass and fuel connectivity are reduced due to processes such as desertification.

The correlation between SCPDSI and multiple broad scale synoptic patterns were examined for the study area using the cross-correlation function (Venables & Ripley, 2002). These included the North American Monsoon, El Nino Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO) and 500 hPa geopotential height anomalies similar to those examined by Gedalof, Peterson, & Mantua (2005). These investigations did not produce any significant correlations.

The possibility for the lack of correlation between SCPDSI and other large scale processes may be the location of the study area. Wise (2010) describes the area as the "Precipitation Dipole Transition Zone". This transition zone lies between two regions (the Southwest and Pacific Northwest) which are highly affected by these larger patterns, but in opposite directions. For example, a positive ENSO anomaly typically brings dry conditions to the Southwest, but brings wet conditions to the Northwest. Since a large portion of the study regions lies in the transition zone between these two regions the effect of these patterns is not clear cut.

Some relationships were found by Collins et al. (2006) between annual area burned and various synoptic indices. The most significant relationship included times in which the Southern

Oscillation Index (SOI) and Warm Phase Atlantic Multidecadal Oscillation (AMO) were opposed 2 years prior; SOI also had a similar relationship. PDO was also significant when it was in phase with Cool Phase AMO during the fire season. These correlations were examined across a much broader time scale (1926-2002) compared to the period used in this study (1984-2009), which may explain why these relationships were not seen during the study period.

MaxEnt does exhibit some difficulty in identifying novel climate patterns different from those used to develop the model. This is not entirely surprising since most models are designed to predict mean behavior, so predictions for patterns which deviate from the mean should be interpreted with a lower confidence than those closer to mean patterns (i.e., cluster centers). The distances calculated during the modeling process (Figure 4) can be used to give some indication of where these novel patterns are located. A prediction made into July 2012 showed very low risk of fire across Utah (Figure 14). The summer of 2012 was a particularly high fire season across Utah so the model results were not satisfactory. The cluster pattern used to develop the model was much smoother and less exaggerated than what was seen in 2012 (Figure 15). As more data become available these extreme patterns can be incorporated and better identified within the model.

For times when the climate patterns resemble those seen throughout the study period, MaxEnt produces useful information regarding the climate conditions throughout the region and the implications for fire risk associated with those conditions. This information could be readily utilized by land managers to inform decisions related to fire conditions. The quality and availability of climate data makes the use of these data for fire condition assessment an attractive option.

Another powerful application of these models is their use in conjunction with long-term projections made by climate models. Given the patterns currently related to wildfires remains

intact, fire risk maps could be produced decades into the future providing an indication of the prevalence of fire-associated climate patterns under different change scenarios. Although such projections would be limited by an assumption of stationary land cover, they would still yield valuable information related to the future of fire occurrence in the region.

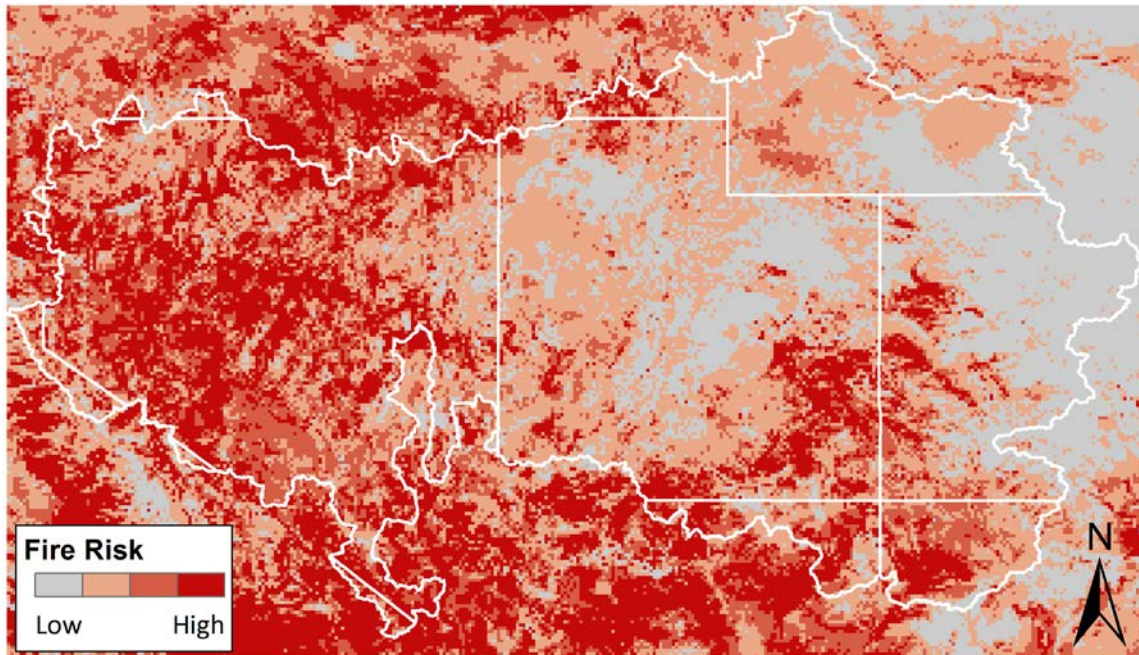


Figure 14. Classified output from model prediction for July 2012. Most of Northern and Central Utah show a low risk of fire when fire risk was actually very high during this period.

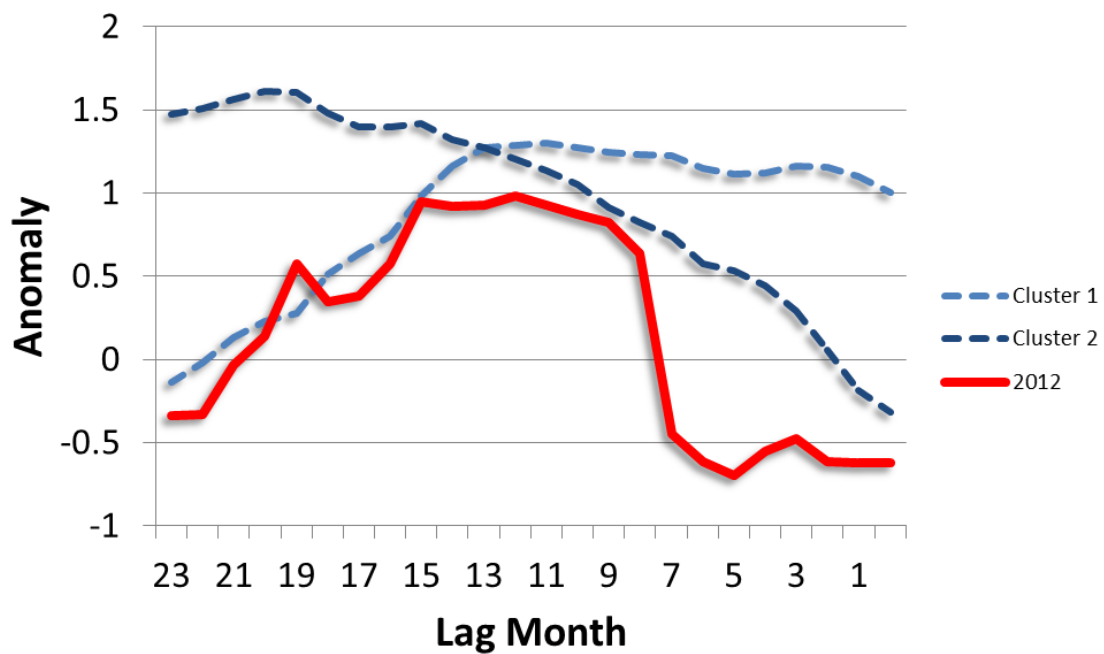


Figure 15. Comparison of centers from Clusters 1 & 2 with the climate pattern observed in Utah during July 2012. The pattern seen in July appears to be an exaggerated composite of the two clusters which contributed to this particular month being predicted with low severity throughout Utah. This prediction conflicts with the extreme fire danger present during this time.

## CONCLUSIONS

Burn severity is a complicated process, both in terms of concept (Keeley, 2009) and measurement (Miller et al., 2009). Elevation was the most important factor for predicting severity. There were suggestions of certain underlying climatic factors affecting how severely a particular area burns (e.g., drought severity of the previous growing season seen in forested locations), but these appear to be overshadowed by factors related to elevation. The study by Dillon et al. (2011) reinforces the importance of local topography and the advantages of the RdNBR algorithm over the dNBR algorithm. Modifications to both the dependent and independent variables should yield clearer results regarding climate's effect on burn severity.

The investigation into fire's relationship with climate within the Interior West yielded interesting results. Distinct climate patterns associated with fire were identified. The relationships between these distinct groups and other environmental factors were also examined. The groups not only varied in terms of antecedent climate patterns, but in land cover and elevation as well. These distinctions may relate to fuel versus climate-limited fire regimes which have unique interactions with climate. More test data will become available as they are compiled for subsequent years allowing for a better assessment of the models' performance during more "normal" fire years. The current results do, however, illustrate the models' utility for predicting and characterizing fire risk now and in the future. Although the story of how climate change will affect fire in the future is nuanced, the climate patterns identified in this study can help us better understand the implications of these changes within the diverse landscapes of the American West.

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